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A NOVEL EFFICIENT DISCRIMINANT COMPONENT ANALYSIS ALGORITHM FOR FACE RECOGNITION

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ABSTRACT

Face recognition is the process of categorizing a person in an image by evaluating with a known face image library. The pose and illumination variations are two main practical confronts for an automatic face recognition system. This paper proposes a novel face recognition algorithm known as EDCA for face recognition under varying poses and illumination conditions. The main aim of this paper is to reduce the feature vector size. The intensity of a face image is normalized to get an illumination normalized image. This EDCA algorithm overcomes the high dimensionality problem in the feature space by extracting features from the low dimensional frequency band of the image. It combines the features of both LDA and PCA algorithms. The experiments were performed on both the Extended Yale B datasets. The experimental results show that the proposed algorithm produces a higher recognition rate than the existing LDA and PCA based face recognition techniques.

Keywords: *Face Recognition, Histogram Equalization, LDA And PCA*

1. INTRODUCTION

Face detection and recognition are one of the most significant uses of the Biometrics-based authentication systems utilizing unique physical or behavioral characteristics [1]. Face recognition, a kind of biometric identification researched in numerous fields such as computer vision, image processing, and pattern recognition is a common biometric process. During the past few decades it has obtained significant consideration because of a large number of application areas such as entertainment, smart cards, information security, law enforcement, surveillance, etc. Face recognition has gained significant consideration from researches in biometrics, pattern recognition field and computer vision areas. Automatic face recognition as a means of human identification has been vigorously studied for more than three decades. The recognition process thoroughly degrades with pose and lighting variations even though the recognition process has been improved substantially under frontal pose and optimal lighting conditions [1]. Sources of errors in automated face recognition algorithms are usually ascribed to the well considered dissimilarities in pose, illumination and expression, collectively known as PIE. Extra factors such as image quality (e.g., resolution, compression, blur), time lapse and occlusion also add to face recognition errors [2]. First, it requires matching facial identities despite changes in lighting and viewpoint and thus requires processing the identity rather than simple image matching [3]. Furthermore, global features are susceptible to variations in facial expressions, poses and occlusions. Another inherent difficulty of all holistic approaches is their belief to the training databases since information about the face discrimination is discriminated by machine learning from the face samples. A representative training database is necessary, which however is not available in many applications [4].

Face recognition algorithms are divided into three categories as follows:

1. Holistic methods: These techniques recognize a face using the entire face image as input and extract the overall features.

2. Feature based methods: The confined facial features are used by these methods for recognition (like eyes, mouths, fiducial points. etc.).

3. Hybrid methods: These methods use both feature based and holistic methods to identify a

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face. These methods have the prospective to offer improved performance than individuals [5].

Three factors concerned in face recognition are illumination, pose and identity. Using a human's face images as example, we address issues involved in each of the three factors.

- Illumination: Different illumination representations exist in the literature, ranging from models for vastly specular objects such as mirrors to models for dull objects.
- Pose: The problem of pose basically quantifies to a correspondence problem. If dense correspondences across poses are obtainable and if a Lambertian reflectance model is more assumed, a rank-1 restriction is implied.
- Identity: This can be attained using subspace encoding, where linear generalization is implicit to integrate the fact that all human faces are alike [6].

Face recognition under variations in illumination and pose has long been recognized as a difficult problem with pose appearing somewhat more challenging to handle than variations in illumination. A direct approach to deal with such images has been done to develop algorithms that are normalized for variations in illumination and then to focus on a solution for pose [8]. Three stages, face representation, discriminative feature analysis and data classification comprise the identification process [9]. In order to make identification independent of imaging circumstances, the aim is to detach intrinsic model factors of the face from extrinsic imaging factors. Many view-based approaches use statistical techniques to address this problem. Head poses that range from frontal to profile views need to be covered in view-based methods by a set of separate models for different views [7].

Pose estimation problems are often made difficult by the fact that illumination is unknown. Thus, it is tremendously significant to expand techniques for face recognition that are robust to dissimilarities in pose and illumination [10]. The major involvement is to treat pose assessment as object recognition using a new in-between body parts depiction planned to spatially confine joints of attention at a low computational cost and high precision. The experiments also bear numerous imminent: (i) artificial depth training data is an outstanding proxy for real data; (ii) scaling up the learning trouble with diverse synthetic data is significant for high accuracy; and (iii) our parts-based approach generalizes even better than an oracular exact nearest neighbor [11].

Facial expression, makeup, eyeglasses, facial hair, weight change and aging are inherent aspects that lead to divergence in appearance. In contrast, extrinsic parameters such as illumination (source brightness, direction and color), camera viewpoint and the camera's radiometric reaction can go ahead to significant image variability [12]. Face recognition across pose, i.e. face recognition where the gallery and probe images do not have the same poses has received very little attention. Algorithms have been proposed which can recognize faces (or more general objects) at a variety of poses. However, most of these algorithms require gallery images at every pose [13]. Pose estimation algorithm can be combined with a multi-view camera setup that is able to process ten video streams in real-time and allows for segmentation of the user in all the camera views [18]. Sampling across pose altering the equivalent illumination cone is approximated by a low-dimensional linear subspace whose source vectors are projected using a generative model. This method desires at the least seven images under diverse lighting conditions for each subject, which is unrealistic for the majority of the applications [14].

This is particularly exciting in our circumstance of images embedded on 3D surfaces, as illumination changes generate deviations on the intensity measurement that can be seen as local anisotropic scaling, for which it still shows a good resilience [15]. There has been a lot literature on illumination invariant feature extraction in the area of face recognition because changeable lighting face recognition is a vital concern for various applications in computer vision.

Although many face recognition techniques have been proposed, there still exists the pose and illumination variation difficulties. In this paper we developed a novel Efficient Discriminates Component Analysis face recognition algorithm to overcome the above mentioned problems.

The outline of this paper is as follows. In section 2 various methods related to this work are presented. Section 3 presents an overview of the proposed face recognition system. Section 4 details the proposed methodology, its various techniques

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and the novel EDCA algorithm proposed in this work. Section 5 illustrates the experimental results and evaluates the performance of the proposed system. Then the conclusion from this work is summarized in section 6. Finally the paper ends with the references.

2. RELATED WORK

J. Shermina and V. Vasudevan [12] have proposed a face recognition method that is robust to pose and illumination differences. For processing the pose invariant image, the Locally Linear Regression (LLR) method was used to create the virtual frontal view face image from the non frontal view face image. Low frequency components of Discrete Cosine Transform (DCT) were used to normalize the illuminated image. In order to recognize the facial images that are both pose variant and illumination variant, the Fisher Linear Discriminate Analysis (FLDA) and Principal Component Analysis (PCA) methods were used. Finally, scores of FLDA and PCA were combined using a hybrid technique based on the Feed Forward Neural Network (FFN). Based on the scores obtained in the initial recognition process, a weight was assigned to the image. The image was recognized based on the weight assigned and the combination of the scores. From the implementation result, it was evident that their proposed method based on the hybridization technique recognized the face images effectively.

Nicolas Pinto and David Cox [16] have demonstrated an extensive feature seeking approach to produce new, more potent feature illustrations in which a large number of complex, nonlinear, multilayer neuromorphic feature representations were arbitrarily produced and monitored to locate those best suitable for the job at hand. In particular, they showed that a brute-force search can produce illustrations that, in mixture with standard machine learning blending techniques, attain state-of-the-art performance on the Labeled Faces in the Wild (LFW) unrestrained face recognition challenge set. These representations outperformed previous state of-the-art approaches in spite of requiring less training data and using a conceptually simpler machine learning back end. They argued that such large-scale-search-derived feature sets could play a synergistic role with other computer vision methods by providing a richer base of features to work with.

Petcharat Pattanasethanon and Charuay Savithi [5] have proposed a novel technique for facial recognition through the implementation of Successes Mean Quantization Transform and extra Network of Winnow with the aid of Eigenface computation. After it had limited the frame of the input image or images from a webcam, the image was cropped into an oval or eclipse outline. Then the image was transformed into grayscale and was normalized in order to reduce color complexities. They also focused on the special features of human facial characteristics such as nostril areas and oral areas. After all the essential aspects were scrutinized, the input image went through the recognition system for facial identification. In some cases where the input image from the webcam did not exist in the database, the user would be notified. Though in cases where the image subsists in the database, that image will be computed for similarity measurement using Euclidean Distance measure from the input image.

Ergun Gumus et al. [17] have presented an evaluation of using various methods for face recognition. As feature extracting techniques benefited from wavelet decomposition and the Eigenface method was based on Principal Component Analysis (PCA). After generating feature vectors, distance classifier and Support Vector Machines (SVMs) were used for the classification step. As test data, they used the ORL face database which was known as a normal face database for face recognition which included 400 images of 40 people. At the end of the overall separation task, they obtained the classification accuracy at 98.1% with Wavelet–SVM approach for 240 image training set.

3. FACE RECOGNITION SYSTEM

The basic concept for face recognition is clearly mentioned in this section (See Figure 1). The common problems in face recognition can be devised as follows: given a single image or a sequence of images, identify the person in the image using a database. Solving the crisis consists of subsequent steps: 1) face normalization, 2) feature extraction, and 3) classification. First, the facial features are extracted from the test image. The features are normally based on color, shape, edge etc. The extracted features are matched to the feature points of the library face images. The recognized result is the best matched feature image [18]. Even though better classification algorithms are used the accurate face recognition, it will be a challenge if any variations occur in illumination and facial profiles. There exists another problem which is the elevated dimension for extracted facial

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features. Recently, face recognition research works are mainly focused on mitigating these problems [10].

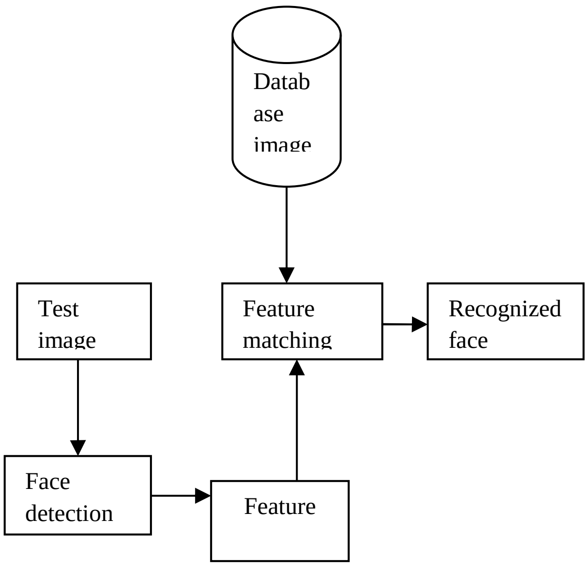

Fig 1. Face Recognition System

3.1. Overview Of The Proposed Approach

The primary concept of this paper is the dimensionality reduction in facial feature space for diminishing the complexity of the extracted features. The proposed algorithm combines the recognition rates of both Linear Discriminant Analysis and Principal Component Analysis algorithms. The proposed algorithm recognizes both pose and illumination invariant face images. Instead of projecting the non frontal face images to frontal pose, in our proposed algorithm we have trained the face images of different illumination conditions and different poses. The recognition performance is improved by illumination normalization. The existing high feature space dimension is alleviated by wavelet transform. Each levels of wavelet transform shrink the size of the image. So, the feature point dimension is highly reduced by our proposed methodology.

4. FACE RECOGNITION

The proposed face recognition work is template based linear subspace face recognition. The combination of both Eigenface and fisherspace will improve the face recognition performance. The high dimensionality feature space leads to computational expense for both training and testing stages in face recognition [19]. The proposed EDCA face recognition algorithm concentrates on the dimensionality reduction in the facial feature vector. The face recognition procedure has the following steps: 1) pre-processing 2) feature extraction, and 3) face recognition.

4.1. Pre-Processing

Image histogram is a graph which signifies grey level frequencies of image. The histogram equalization is a technique that spreads out intensity values over the whole scale to attain a uniform histogram which in turn progresses the contrast of an image. The idea of the pre-processing module is to reduce or get relief of some of the disparities in face due to illumination. Normalization of the face image is used to develop the recognition performance of the system. Pre-processing is vital as the robustness of a face recognition system seriously depends on it. By using the normalization procedure, system robustness against scaling, posture, facial expression and illumination are all improved.

4.1.1. Illumination normalization

The variation in illumination is an important factor which affects the recognition rate of a face recognition system. This problem is solved by normalizing the illumination [20]. The existing illumination normalization techniques are based on wavelet transform by applying various filters, etc. [21]. The proposed illumination normalization is intensity normalization.

In this approach, face images are pre-processed using some image processing methods to normalize the images to become stable under diverse lighting circumstances. Extrinsic factors like varying illumination conditions could pose a problem in face recognition. These illumination problems can be solved using illumination normalization.

Algorithm for Normalization:

1. Calculate the minimum (I_{min}) and maximum (I_{max}) intensity value of the images.

2. Range the image value by using $I_{range} = I_{max} – I_{min}$

3. Assign the minimum (N_{min}) and maximum (N_{max}) normalized intensity values for normalizing the image.

4. Calculate normalization range by $N_{range} = N_{max} – N_{min}$

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5. Scale and calculate the normalization illumination value for every pixels of the image:

$$I_{scale} = (I_{initial} - I_{min}) / I_{range}$$

$$I_{norm} = (N_{range} * I_{scale}) + N_{min}$$

To the best of our knowledge, an ideal way of solving the illumination variation problem is to normalize a face image to a standard form under uniform lighting conditions. In fact, the human visual system usually cares about the main features of a face; such as the shapes and relative positions of the main facial features and ignores illumination changes on the face while recognizing a person.

4.1.2 Edge detection

Edge enhancement is done to highlight the fine details in the original image. The perceptibility of edges and small features can be enhanced by increasing the amplitude of the high frequency components in the image. To emphasize facts, we multiply each element in the detail coefficient matrices with a scale factor. As the decomposition level increases, the contrast and edges are enhanced further. A normalized image is obtained from the modified coefficients. This normalized and reconstructed image is sent to the next level for further contrast and edge enhancements using the canny edge detector algorithm.

Canny Edge Detector Algorithm

Canny edge detector is the optimal and extensively used algorithm for edge detection. When compared to other edge detection techniques like Sobel, etc. the canny edge detector offers robust edge detection, localization and linking. To put it in simpler terms, it is a multi-stage algorithm. The kernels concerned in the canny edge detector algorithm are conferred in detail in this section. At each stage, for calculating the output pixel at an exact row, we require input pixels at rows below and above. Thus, the outputs at the first and the last rows are indeterminate. The same occurs in the case of columns too. Thus, the size of the suitable pixels in the output reduces after each step. To include this, the output width and height and the output buffer's position vary after each step. This is demonstrated in each stage as API argument regulations [22].

Steps in Canny Edge Detection:

1. Smoothing: Blurring of the image to remove noise.

2. Calculating gradients: The edges must be noticed where the gradients of the image has big magnitudes.

3. Non-maximum repression: Simply local maxima should be marked as edges.

4. Double thresholding: Probable edges are determined by thresholding.

5. Edge tracking by hysteresis: Last edges are determined by restraining all edges that are not connected to a very definite (strong) edge [23].

4.2. Feature Extraction

4.2.1 principal component analysis (pca)

The PCA algorithm is a template based face recognition technique. It is one of the most commonly used face recognition techniques. The eigenface method is motivated by face reconstruction based on the PCA. The main principle of the PCA algorithm is to reduce the high dimensionality dimension vector into an intrinsically low dimension feature vector. The projection of face images into the principal component subspace attains information compression, decorrelation and dimensionality diminution to make decision making easy [24]. The PCA algorithm generates a eigen face for a face image by joining the eigen vectors [25]. Principal component analysis (PCA) is one of the most accepted techniques for reducing the number of variables used in face recognition. In PCA, faces are represented by means of Eigen faces which is a linear combination of weighted eigenvectors. These eigenvectors are attained from the covariance matrix of a training image set known as basis function. In this way we can obtain Eigen faces for each image in the training set. Eigen faces takes benefit of the resemblance among the image pixels in a dataset by means of their covariance matrix. A new face space is defined by these eigenvectors for representing the images. To fix the requisite notation, the following symbols are used [25].

Let training image set I_t consist of M images each having size m×n pixels. Using the usual row appending technique convert each of the images into m×n dimensional column vectors.

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$$I_t = \{i_{t1}, i_{t2}, \ldots\ldots\ldots, i_{tm}\} \quad (1)$$

Covariance matrix C_M of the training image set tm is calculated by using the equation given below:

$$C_M = \frac{1}{M}\sum_{m=1}^{M}(i_{tm} - \bar{i})(i_{tm} - \bar{i}) \quad (2)$$

Where $\bar{i}$ is the mean vector of all images in the training set, C_M is the covariance matrix and tm is the training image. Eigen value and eigenvectors of covariance matrix is calculated using equation (2):

$$E = (i_{tm} - \bar{i}) \times v \quad (3)$$

Where m = 1, 2… M, $\bar{i}$ is the mean vector of all the images in the training set tm. The Eigenvectors originated, E have a face like appearance, and they are termed as Eigen faces. Sometimes they are also known as Ghost Images due to their peculiar appearance. After the face space has been built, the feature vectors are created as a linear combination of the eigenvectors of the covariance matrix. An image is projected into the face space with the aid of following equation (5).

$$P_m = E^T \times (i_{tm} - \bar{i}) \quad (4)$$

Where P_m is the projected image and m = 1, 2 ,…, M are the weight vectors associated with the eigenvectors in c. One can try out with the number of eigenvectors to calculate the weights, usually only a few amount offers adequate information for sufficiently representing the images in the face space. For recognition of an unknown face or a test image tm, normalize it by performing subtraction from the mean vector of all images in the training set. Then using equation (3) project the normalized test image as shown in the following equation (5):

$$T = E^T.D \quad (5)$$

where D is the normalized test image. After the feature vectors (weight vector) for the test image have been found, the next step is to classify it. For classification, we could basically use the Euclidean distance classifier (equation 6).

$$e_d = \min \|T - P_m\| \quad (6)$$

Where m= 1,2,…,M, T is the test image, P_m is the projected image and e_d is the Euclidean distance. If the distance is little, we state that the images are alike and hence we can decide with the most similar images in the database is.

4.2.2. Linear discriminant analysis (lda)

The linear combination of fisher's discriminant analysis vectors is called the fisher face. This algorithm increases the ratio of the within-class variance and the between-class variance. The optimal linear function derived by this LDA algorithm maps the feature values to a specific feature space [26]. The principle of discriminant analysis is to categorize objects into a number of classes based on a set of features that illustrate the objects. Imagine that the classes are linearly separable and then the linear discriminant model (LDA) can be used. Linearly separable recommends that the groups can be alienated by a linear combination of features that express the objects. If there are only two features (independent variables), then the separators between groups of objects will turn out to be lines. If there are three features, then the separator is a plane and if the number of features is greater than three, the (5) separators become a hyper-plane. Linear discriminant analysis (LDA) is a frequently used method for the purpose of classification of data and for its dimensionality reduction. It is also known as fisher's discriminant analysis and it searches for those vectors in the fundamental space that best distinguishes among classes. The purpose of LDA is to carry out dimensionality reduction while conserving a lot of the class discriminatory information. The objective of LDA is to increase the between-class scatter matrix measure while diminishing the within-class scatter matrix measure.

In the existing system, a two-stage PCA+LDA method was proposed, where PCA is used to and make the within-class scatter generate (6) by projecting images from the original image space to the low-dimensional space. The first dimensionality reduction using PCA can also eliminate the discriminant information that is useful

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for classification. The most efficient technique plans the between-class scatter into the null space of the within-class scatter and prefers the eigenvectors equivalent to the biggest eigenvalues of the relocated between-class scatter.

4.3. Efficient Discriminant Component Analysis (Edca) Face Recognition

The proposed EDCA algorithm mainly considers the dimensionality problem in the feature space. Instead of taking features from complete face image pixels, the features are extracted from the frequency components only. Then the extracted frequency component features are reduced by the LDA and PCA algorithms. The proposed EDCA algorithm combines the recognition rates of both LDA and PCA techniques.

Figure 2 shows the proposed methodology for face recognition. It consists of two stages namely the training stage and the testing stage. In the training stage the face images with different illuminations are taken. The preprocessing steps are histogram equalization, illumination normalization applied to normalize the illumination of the images. Then the proposed EDCA algorithm is applied on the illumination normalized image. The extracted feature vector is saved in the feature vector set. In the testing stage the unknown test face image with different illumination is taken. The preprocessing feature extraction is applied to that image and the Euclidean distance between the extracted feature vector and the saved feature vector dataset is found. The test image will be recognized by the two classification results such as match and no match where match denotes the face image which is having a Euclidean distance value nearer to zero. If there is no image in the dataset with zero Euclidean distance with the test image feature then the algorithm results that no match is found.

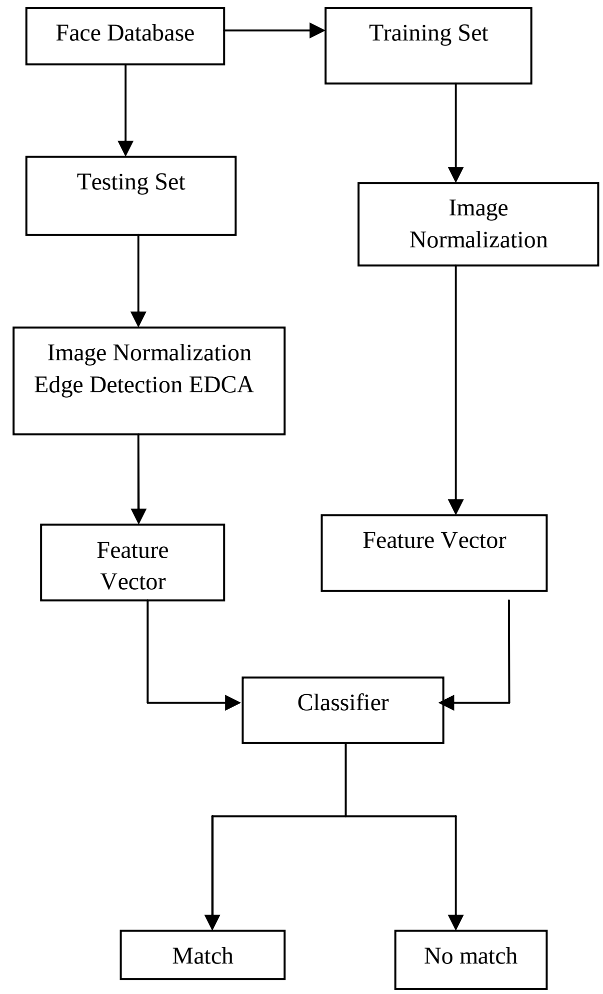

Fig 2. Flow chart of proposed face recognition method

4. 3.1 wavelet transform

Wavelet is a mathematical tool. Wavelets let complex images to decay into simple structures at diverse positions and scales and then reconstruct it with high accuracy [26].

$$F(x) = \sum_{n=0}^{\infty} a_n f_n(x) \qquad (7)$$

The wavelet transform of an image F is shown in equation (8) where f(x) are simple functions and a_n are coefficients.

The concept of wavelet transform is to represent any function f(x) into superposition of wavelets. Each superposition has a scale level. Thus the

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wavelet transform changes the image into one of different resolution. It consists of a mother wavelet and a scaling function. The wavelet transform decomposes the image into spatial domain and frequency domain. Figure 3a shows the 3 level wavelet transformation of an image. Figure 3b is an example result of 3 a level wavelet transformation of an image. The purpose of wavelet transform in our approach is to reduce the dimension. So the feature dimension also reduced. In the proposed algorithm daubechei wavelet transform is applied and the fourth level frequency component features are extracted.

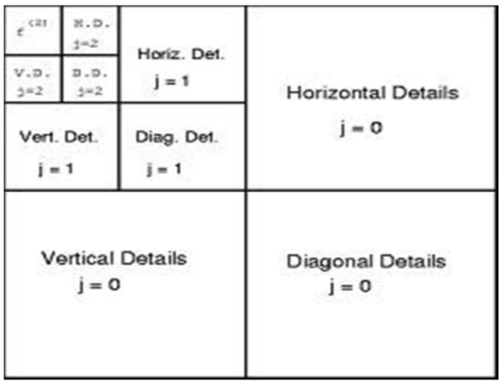
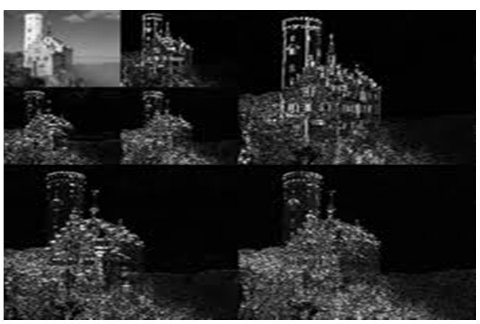


Fig. 3a Wavelet Transformation Details



3b Three Level Wavelet Transformation

4.3.2. Combination of PCA and LDA

Training stage

This section discusses about the synthesis of both LDA and PCA methods. Our proposed algorithm utilizes the recognition concerts of both. During the training phase the image features are extracted by both PCA and LDA algorithms separately and then the distance between the trained image features and the dataset features are found by the Euclidean distance. Thus the face image is recognized with the minimum distance in dataset images. Instead of projecting a non-frontal pose image, we proposed a trained system in which for a single face image we have trained six different poses of the same image to a single class.

Testing stage

Test face images are first preprocessed by the histogram equalization algorithm and then the illumination is normalized by the proposed normalization algorithm. Then the features are extracted by the proposed EDCA algorithm. The match results of both LDA and PCA are checked with the recognition rules mentioned in table 1.
Similarly, if any one of the LDA or PCA recognition results is correct, then our technique gives a correct recognition output. If, and only if both LDA and PCA recognition results are wrong our approach's result is a wrong match.

Table 1 Recognition Rule Set

Recognition factors	LDA	PCA	Recognition decision
Correct recognition	T F T F	F T T F	Correct recognition
Wrong recognition	T F T F	F T T F	Correct recognition
No result	T F T F	F T T F	Correct rejection

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Fig 4 EDCA algorithm

Pseudocode
Input: Test face image
Output: Recognized image from dataset
Function: Step-1 Pre-process the image by histogram equalization Step-2 Illumination normalization by the technique mentioned in section 4.1.1 Step-3 Apply 3 level wavelet transformation and select the 4th sub-band medium frequency coefficients Step-4 Apply LDA and PCA feature reduction techniques Step-5 Match the classification results of both LDA and PCA by the feature decision rules. Step-6 Recognize the image by the Euclidean distance classifier

The detailed explanation for the proposed EDCA algorithm is explained in this section.

The first step of the proposed algorithm is preprocessing, then in the second step the illumination of the face image is normalized by the normalization technique mentioned in section 4.1.1.

The third step is to apply 3 level wavelet transformation on the illumination normalized image and the 4th sub-band is selected. In the fourth step, the LDA and PCA feature reduction techniques are applied on the extracted feature set. The classification results of both LDA and PCA are matched by the feature decision rules in the fifth step. In the sixth step, the face image is recognized by the Euclidean distance classifier. The Euclidean distance between two feature vectors is found by the following ways.

5. EXPERIMENTAL RESULTS

The proposed EDCA algorithm is experimented on an Extended Yale B face dataset of profile and illumination invariant faces. Our approach is compared with LDA and PCA face recognition techniques. The parameters such as accuracy, precision, recall and F-measure values are compared. From the experimental results, we can conclude that our EDCA face recognition algorithm outperforms the LDA and PCA face recognition techniques. The recognition accuracy of our proposed EDCA algorithm is almost 99.9%.

Performance Measures:

Accuracy

(A) = (TP+TN)/(TP+FP+FN+TN) (8)

Precision (P) = TP/(TP+FP) (9)

Recall (R) = TP/(TP+FN) (10)

F measure (F) = (2 * P * R)/(P+R) (11)

Where TP is True positive, TN is True Negative, FP is False Positive and FN is False Negative.

The experiment is conducted under three different feature vector dimensions of size, viz. 1x22, 2x22 and 3x22. The performance of the EDCA face recognition algorithm is measured by the performance measures such as accuracy (equation 8), precision (equation 9), recall (equation 10) and f measure (equation 11). The results of which are plotted in graph 1, graph 2 and graph 3 respectively. The proposed algorithm is compared with the existing LDA and PCA face recognition techniques.

Table 2 Comparison Table For 1 X 22feature Vector Dimension

Algorithm	Accuracy	Precision	Recall	F-Measure
LDA	0.725	0.68571	1	0.81356
PCA	0.95	0.92308	1	0.96
EDCA	0.975	0.96	1	0.97959

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Table 2 represents the performance measures of the LDA, PCA and EDCA algorithms at the feature vector dimension of 1 x 22.

Table 3 Comparison table for 3 x 22 feature size

Algorithm	Accuracy	Precision	Recall	F-Measure
LDA	0.825	0.77419	1	0.87273
PCA	0.875	0.82759	1	0.90566
EDCA	0.9	0.85714	1	0.92308

Table 4 Comparison table for 2 x 22 feature size

Algorithm	Accuracy	Precision	Recall	F-Measure
LDA	0.85	0.8	1	0.88889
PCA	0.9	0.85714	1	0.92308
EDCA	0.975	0.96	1	0.97959

Tables 3 and 4 represent the performance comparisons of the LDA, PCA and EDCA algorithms.

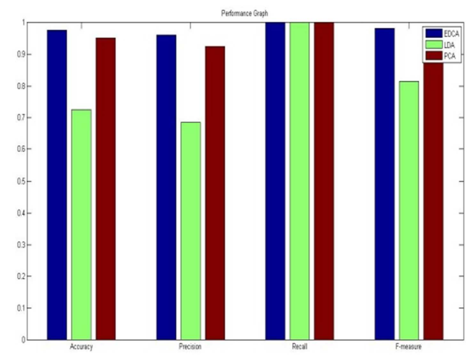

Fig. 5 Comparison graph for accuracy, precision, recall and F-measure of LDA, PCA and EDCA (proposed) under 1x 22 dimension feature space

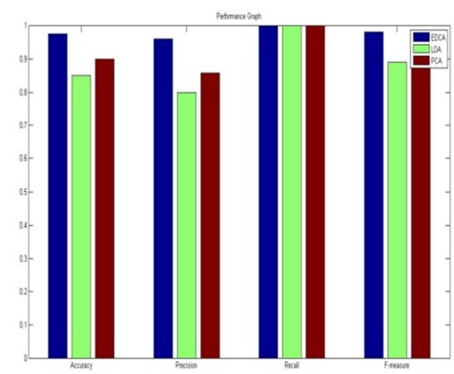

Fig. 6 Comparison graph for accuracy, precision, recall and F-measure of LDA, PCA and EDCA (proposed) under 2x22 dimension feature space

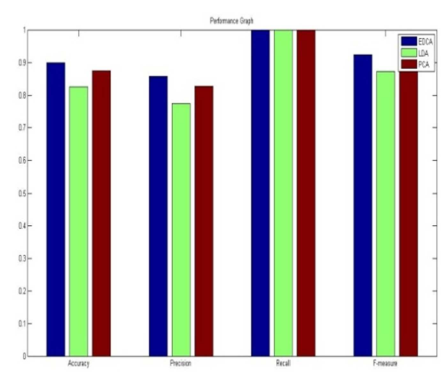

Fig. 7 Comparison graph for accuracy, precision, recall and F-measure of LDA, PCA and EDCA (proposed) under 3x22 dimension feature space

From the experimental results, we can conclude that our proposed EDCA face recognition algorithm

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outperforms the existing LDA and PCA face recognition techniques.

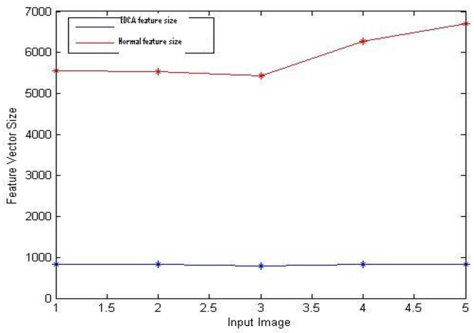

Fig. 8 Feature Vector Size Comparison

Figure 8 is the comparison graph of the feature vector size of the proposed EDCA algorithm i.e. feature extraction from the wavelet transformed image and the feature extraction from a normal face image. From the graph we can conclude that the feature vector size of the EDCA algorithm is tremendously lower than the feature vector extracted by the existing feature extraction techniques. Even though the wavelet transformation reduces the resolution of the feature vector size, the face recognition accuracy of the EDCA algorithm is better than the existing face recognition techniques. The future direction of this work is to extend this face recognition EDCA algorithm for various occlusion images.

6. CONCLUSION

In this paper we proposed a novel Efficient Discriminant Component Analysis algorithm for face recognition. The proposed technique overcomes the drawbacks of the existing LDA and PCA approaches. Though the PCA algorithm is mostly used in face recognition, it has the shortcoming of poor discriminatory power and the computational load is also high. The inherent drawback of the LDA algorithm is the singularity problem i.e. the LDA's performance is poor when all the scatter matrices are singular. To overcome these drawbacks, we propose a novel EDCA face recognition algorithm. In this work, the high dimensionality in face features is considerably reduced by extracting features from the medium frequency components of the face image. By applying wavelet transformation, the resolution of the image is reduced. The recognition results of LDA and PCA are merged to produce the best recognition results. The proposed algorithm is experimented on an Extended Yale B dataset. The results show that the proposed algorithm yields 99.9% recognition accuracy for profile and illumination invariant face images.

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